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Maximizing Online Learning Intervention Strategies through Powerful Learning Analysis Techniques

Simin Cai

School of Education, Faculty of Social Sciences and Humanities, Universiti Teknologi Malaysia, Malaysia

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Abstract: Online learning is increasingly important for lifelong learning. Analyzing learner's behavior of using learning analytics tools can help improve engagement and quality. In this paper, we investigate the impact of these tools on teacher interventions in online collaborative learning. Based on different intervention models, this paper designs matching experiments to investigate the influence of learning analysis tools on teachers' intervention behavior. The study found that learning analysis tools in online collaborative learning had a significant impact on teachers' intervention behavior, and teachers in the experimental group were significantly higher than those in the control group in the total frequency of intervention, cognitive intervention and personal intervention. In addition, this paper further puts forward some suggestions on the use of learning analysis tools in teaching practice, which provides a new way to adapt to the era of big data education and teaching.

Keywords: Online learning; Learning analysis; Instructional intervention; Intervention strategies; Self-regulated learning.

1 Introduction

With the speedy improvement in the world of technological know-how and the mindset of governments and establishments in the direction of digitization in all their services, the Kingdom of Saudi Arabia has been eager to undertake the thinking of authorities' digital transformation by using changing common tactics with digital ones [1]. We are in technology, where large information and synthetic Genius are rising. The New Media Consortium's (NMC) Horizon Report sees the future of Research as dominated by learning analytics technologies, which apply data analytics to improve instructional services and change the role of the learner from a data consumer to a creator. The report states that learning analytics is the collection of data from learners' learning processes through loosely coupled data collection tools and the use of relevant technologies to analyze them for real-time evaluation of courses and instruction [2]. The Society for Learning Analytics Research (SOLAR) organizes the annual international conference LAK on the theme of "Learning Analytics Technology and Knowledge," which attracts experts in learning analytics-related fields from various countries around the world, covering various directions such as learning science, data science, computer science, etc. Establishing SOLAR is important for rapidly expanding the emerging field of learning analytics. The establishment of SOLAR has also played a great role in boosting the rapid expansion of this emerging field of learning analytics.

Technology means of distance education programs have evolved significantly, causing the spread of distance education and enforcement of technological means programs [3]. The increasing integration of Internet technology and education has brought the advantages of online education to the fore. Compared with traditional classroom teaching, online education focuses more on the learning process of the learners and fully embodies the concept of "learner-centered" education, in which learners have more autonomy and can learn at their own pace according to their own situation. Carried out an unprecedented large-scale online teaching and learning, and online education once again became a hot topic of national attention [4]. However, at the same time, online education has revealed many drawbacks, and it still faces numerous challenges in its development process. Many online education courses are simple classroom moves, where teachers focus only on the presentation of teaching content and require learning to adapt to teaching while neglecting the role of teachers" teaching behaviors in facilitating students" learning behaviors. Educators should foster relationships, share information, and collaborate during professional development to maximize the benefits. The quality of existing pre-service teacher preparation programs should also be examined [5].

Due to a series of problems in the traditional learning environment, such as the difficulty of collecting data on learners" behavior in the learning process, the single means of learning intervention, and the complexity of the intervention process, the operability of learning intervention is poor, and it has received the attention of scholars and experts. Still, there is a lack of relevant Research [6]. The emergence of learning analytics technology undoubtedly provides an objective basis for learning interventions, and teachers can monitor learners" learning behaviors in real time with the help of relevant technologies, and form visual learning reports through statistical analysis, so as to assess learners" learning status, discover

*Corresponding author e-mail: stefaniecsm@163.com

their potential learning problems, and take certain intervention measures to solve various problems encountered by students in the process of learning, so as to achieve the maximum avoidance of learning risks and improve learners" learning behaviors [7]. In this process, teachers can also continuously improve their teaching design and teaching methods based on learners" learning, and for learners, the visual learning reports presented by using learning analytics can help promote learners" self-reflection and self-regulation, and learners can continuously improve their own behaviors in light of the problems and actively participate in course learning to further realize effective learning.

2 A Review of the Literature on Learning Analytics Techniques and Learning Interventions

2.1 Research Related to Learning Analytics Technology

Learning analytics is a new technology that emerged with big data and is considered the third wave of educational technology development. Since the introduction of learning analytics, foreign scholars have been dedicated to exploring and researching this technology with great development potential, and after years of Research and practical exploration, foreign Research on learning analytics has been rich and mature.

2.1.1 Research on the Nature of Learning Analytics

Since then, learning analytics has attracted the attention of scholars and has been rapidly developed [8]. The author has sorted out the representative views of foreign scholars on the definition of the concept of learning analytics, as shown in Table 1.

Table 1: Representative views on the definition of learning analytics

Presenter	Time	Opinion
Lockyer, Heathcote & Dawson[9]	2013	Learning Analytics is the application, processing, and analysis of dynamic information about learners and their learning environment to model, predict and optimize the learning process and environment in real-time and make accurate educational decisions.
Cummins, M., Estrada, V., Freeman, A., and Ludgate, H. [10]	2013	Learning analytics uses learner-related data to build better instructional approaches to address struggling learners and inform administrators, policymakers, and legislators about the effectiveness of program practices.
Johann Ari Larusson, Brandon White [11]	2014	Learning Analytics is the collection, analysis, and application of educational data to assess the community's behavior in the education field.

2.1.2 Research Related to the Elements and Process Models of Learning Analytics

In order to clarify the elements and links within learning analytics, many foreign scholars have tried to explore the building elements and analysis process of learning analytics in the context of actual research environments to solve the problems in the practical application of learning analytics. For example, Kaendler proposes that learning analytics contains five major elements: data collection, data analysis, student learning, stakeholders, and intervention. He believes that the core of learning analytics is to collect and analyze relevant learning data of learners and provide feedback on learning analytics results to stakeholders (teachers, students, or instructional administrators) so that teachers can make precise policies and provide targeted interventions and guidance, students can self-regulate their learning based on their learning, and instructional administrators can adjust instructional decisions and optimize instructional management on this basis [12].

Ferguson et al. proposed a learning analytics lifecycle model based on a large number of relevant conference materials and research results, as shown in Figure 1. The model consists of four parts: learning environment, big data, analysis, and action, and is a closed loop, where the end of one cycle is also the beginning of the next learning analytics cycle [13]. Dyckhoff, president of the Learning Analytics Research Association, through years of research practice, proposed a learning analytics process model based on a systematic approach in terms of data sources, data types, analysis methods, and predictions, as shown in Figure 2, which emphasizes the analysis and visual presentation of learner-related learning data to grasp the learning status of learners in real-time and diagnose possible learning problems of learners. Thus, it provides learners with timely and effective interventions to help learners complete their learning tasks and achieve improved learning outcomes. This model has laid an important foundation for subsequent Research on learning analysis-related models [14].

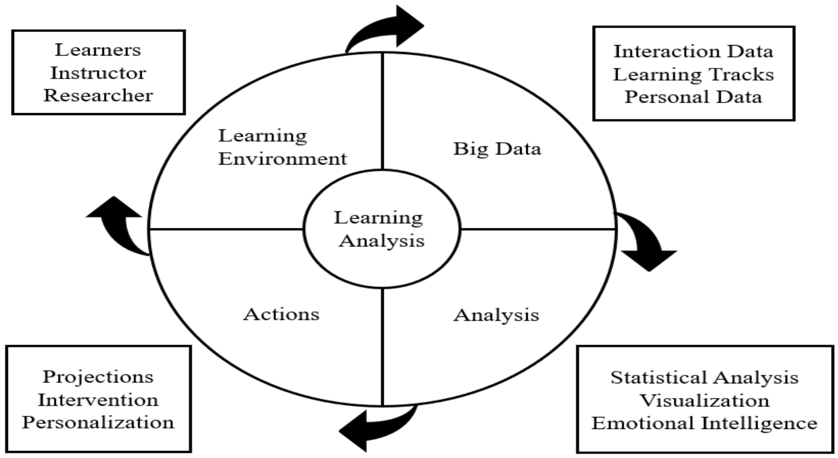

Fig. 1: Ferguson et al.'s learning analytics lifecycle model based on relevant conference materials and research results

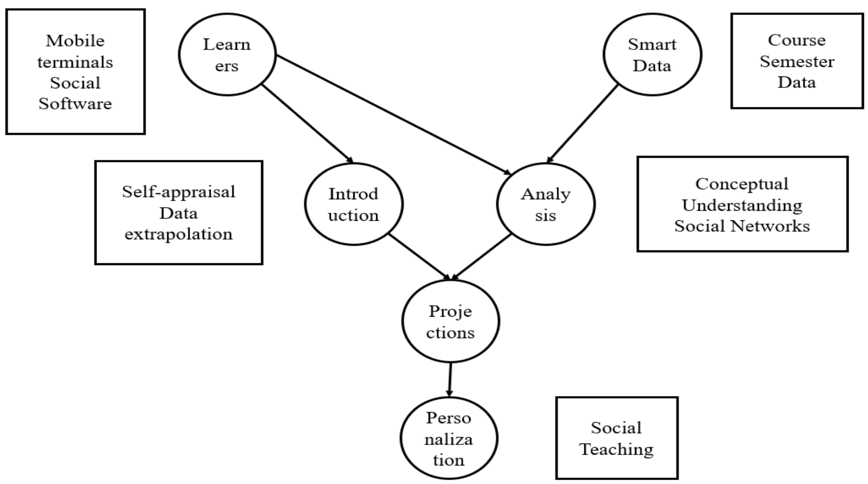

Fig. 2: Dyckhoff's learning analytics process model based on a systematic approach

2.1.3 Research Related to the Practical Application of Learning Analytics

Theoretical Research on the nature and elements of learner analysis and its process model has provided important guidance for the practical study of learning analytics. Based on BlackBoard, Leah et al. conducted an empirical study using learning analytics technology to collect and analyze learners" learning behavior data, visualize learners" online learning behavior, and analyze learners" online learning activity. The visual representation of learners" behavioral performance and the analysis of learners" online learning activity enable instructors to accurately identify learners who are at risk for learning and provide timely and targeted reminders and interventions [15]. Purdue University tracks data related to learners" personal characteristics, learning experiences, and learning inputs. It builds course signal lights based on them, which are divided into three colors: red, yellow, and green, and displays the signal light colors on individual learning homepages so that teachers can make timely teaching interventions to students through the signal light colors, provide feedback to learners on their learning status using emails, and give students reasonable textual learning The teacher can provide timely instructional interventions to students via signal colors, feedback to learners on their learning status using email, and give students sound text-based learning advice and personalized learning guidance. Northern Arizona University has developed a performance evaluation system that analyzes student behavior data, test scores, etc., and uses them as a basis for grading students" learning, sending emails with suggestions and interventions for learners with learning problems, so that they can understand their current learning progress and status and improve their learning behavior and performance. Khan Academy uses learning dashboards to reflect learners" progress and knowledge and provides feedback to teachers, students, and parents through visual reports. Teachers can adjust their teaching activities and provide targeted instruction to students, and parents can gain insight into their students" learning and provide appropriate assistance. The dashboard also allows learners to visualize their learning status and self-regulate their learning according to the actual situation.

2.2 Research Related to Learning Interventions

Learning interventions are activities that can only be carried out under certain conditions. They are used to record and analyze learners" behavior in online learning, such as the time they log in, the length of their study, the time they complete tasks, the number of interactions, etc., so that instructors can clearly understand students" learning crises in the learning process, and appropriately increase interventions or adjust teaching methods to improve learners" learning outcomes to a greater extent. In the traditional way of teaching, teachers only observe students in the classroom, mainly rely on stage test scores as a criterion and implement interventions after the test: however, the intervention effect can be maximized when teachers can judge students based on their learning behavior data, The questionnaire format is also feasible for collecting emotional data such as depression, anxiety, and slackness, and instructors need to provide learners with opportunities to create more opportunities to express unstructured data information about learners" motivation and attitudes toward learning.

2.2.1 Learning the Meaning of the Intervention

Before the study, the author sorted out the meaning of "intervention." In Chinese, intervention is the potential to interfere, intervene, or take part in the affairs of others; in English, intervention is the capability to take part in the affairs of others and is translated as "intervene"; it is the capability to interfere, to relate, or to intervene in the affairs of others and is translated as "correlate."

Berth et al. scholars classified online learning interventions into managerial intervention, instructional thousand pre, and technological interventions according to the identity of the intervener" [16]. Meixia Ding et al. classified instructional and social interventions from the nature of interventions, individual and class interventions from the scale of interventions, and manual and automatic interventions from the subject of interventions [17]. Chao Zhang was divided into plenary, group-oriented, and individual interventions according to the intervention target; and preparatory, formative, and post-regulatory interventions according to the time sequence.

2.2.2 Typical Models of Traditional Learning Interventions

"The Response to Intervention (RTI) model is an approach to accurately assess and intervene with students with learning disabilities that emphasizes multiple levels of assessment and intervention implemented by the teacher or researcher during instruction. Since its introduction in the 1960s, the model has been more widely used in elementary and secondary schools, especially in the field of special education ensures that each student receives appropriate learning support through three levels of intervention, and there can be multiple interventions at each level" [18]. As shown in Figure 3, the first level is a regular instructional and screening process for all students, where teachers can find "struggling students" by comparing data collected from multiple exams with instructional objectives, or by directly screening out slow learners from the data. The second tier helps students who do not respond adequately to learning interventions in the first tier. The third tier provides intensive individual intervention for students who do not progress significantly in the first two tiers. As a typical intervention model in a traditional teaching environment, RTI's three-level intervention concept provides an important reference and reference for constructing this study's online learning intervention model.

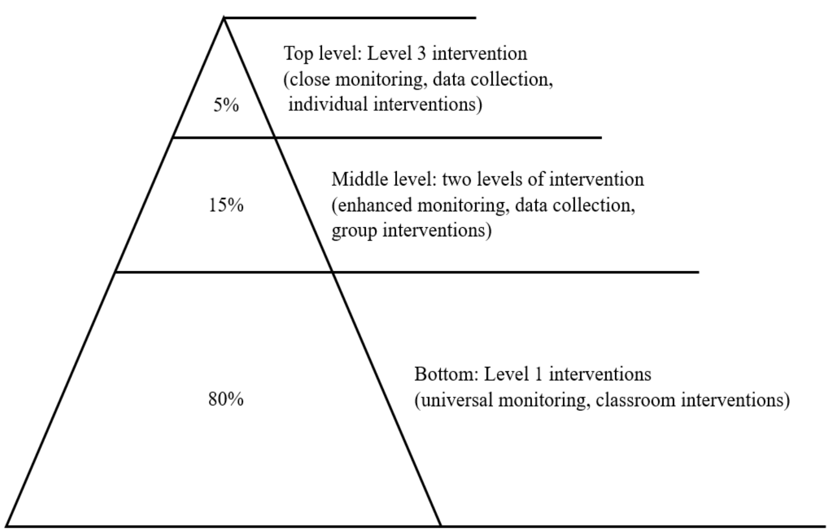

Fig. 3: The Response to Intervention (RTI) model

The RTI model tends to be more of a simple framework, originally used to identify learning difficulties and improve academic performance and applied primarily in special education and general schools. As the trend of special education and general education gradually became integrated, the RTI model began to expand in its application and gradually began to involve every student.

2.2.3 Derived Models of RTI

Since the RTI model was proposed, many educational researchers have explored its application through a large number of practices. The PBIS model, also known as the Problem-Based Positive Behavior Intervention and Support model, is based on the RTI model's three levels of intervention and is designed to enhance appropriate intervention behaviors through instruction. This model follows the core congruency principle of providing a range of interventions based on the student's level of need, and it applies to the improvement of behavior problems, as shown in Figure 4. Compared to the RTI model, the PBIS model is more flexible regarding the proportion of interventions at each level, specifying specific goals for each level of intervention, but it is still a simple framework that does not address specific intervention methods and strategies.

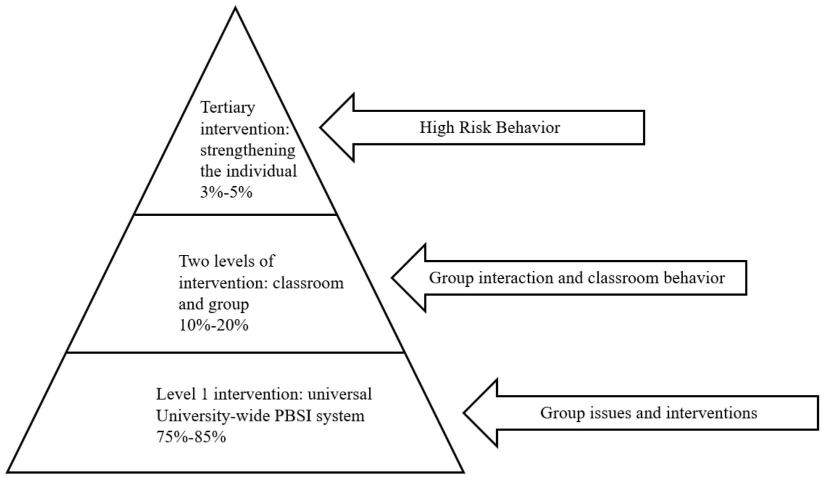

Fig. 4: Problem-Based Positive Behavior Intervention and Support (PBIS) model

The other is the Equivalent Fraction Intervention model, which concretizes the RTI model's idea of tiered intervention and applies it to specific disciplines [19]. The Equivalent Fraction intervention (EFI) model does not show learning progress, and the learning intervention strategies used are the same for learners at the same level when providing learning interventions. As shown in Figure 5, the Equivalent Fraction Intervention model concretizes the intervention ideas of the RTI model and applies them to subject-specific content, which provides a reference for subject-specific learning interventions but does not take into account the individuality of students and cannot provide different interventions for each learner.

The researcher applied the Equivalent Fraction Intervention model to elementary school mathematics and explored how to effectively use the concept of peer fractions to guide learning interventions when students are struggling with mathematics. The results of this study suggest that the Equivalent Fraction Intervention model is effective for interventions in mathematics instruction.

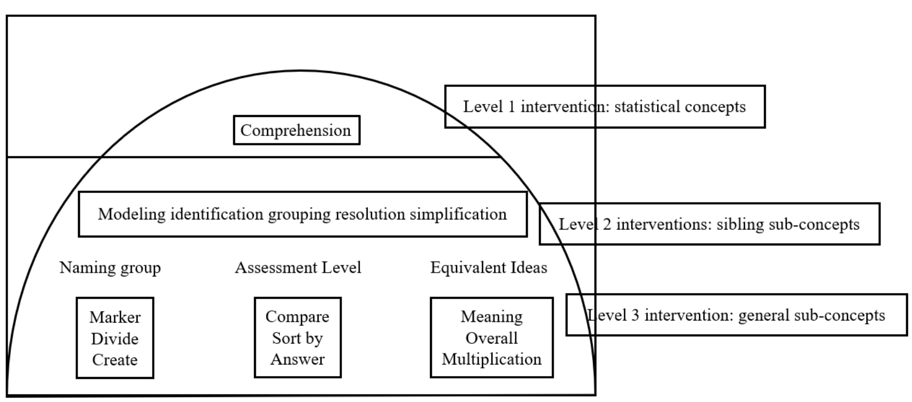

Fig. 5: Equivalent Fraction Intervention (EFI) model

In addition, in recent years, some domestic scholars have also conducted preliminary discussions on the construction of learning intervention models in the technological environment, considering the development of educational theory and practice. Chao Zhang constructed a learning intervention response model and an intervention decision model in the learning activities of distance training, in which the intervention response model consists of three progressive levels of primary intervention, secondary intervention, and tertiary intervention" [20]. Jass proposed a learning intervention model based on big educational data, which includes identifying learning states, matching intervention strategies, implementing intervention strategies, and analyzing intervention effects centered on an intervention engine [21].

3 Study Design and Implementation

3.1 Learning Analytics Tools

In this study, the KBS-T learning analytics tool was used to support teachers' intervention in online collaborative learning [22]. Based on the existing Research, the KBS-T learning analytics tool visualizes learners' online collaborative learning performance by extracting learning performance indicators from three dimensions: knowledge processing, behavior patterns, and social relationships, and by mining collaborative learning process data. As shown in Figure 6 on the next page, the KBS-T learning analysis tool collects and analyzes learners' collaborative learning behavior data in Moodle platform in real-time and presents the visualization of three dimensions of knowledge processing, behavior patterns, and social relationships in the individual level and group level, respectively [23]. Teachers can always combine the content of students' collaborative discussions with the multidimensional visualization presented by KBS-T to understand the learning progress of the learning group and its members, identify learners' problems in collaborative learning and give timely and appropriate interventions [24]. Teachers can view the learning performance visualizations at the group level or individual level in three dimensions: knowledge processing, behavioral patterns, and social relationships, respectively. At the group level, teachers can choose to view the collaborative learning performance of single or multiple groups to identify individual problems in the collaborative learning process and summarize the common problems of multiple groups, and then intervene appropriately in the collaborative learning of a group or the whole class [25]. At the individual level, the teacher can also customize one or more learners to see their performance in the collaborative learning process, to understand their knowledge progress, behavior patterns, and social relationships, to identify problems, and provide appropriate interventions for individual learners [26].

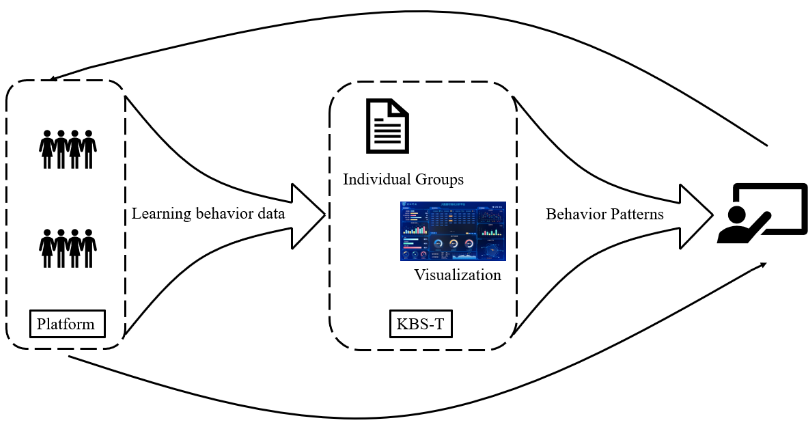

Fig. 6: Teacher intervention process supported by the KBS-T learning analysis tool

3.2 Research Subjects and Process

This learns about using a quasi-experimental lookup technique with 31 pre-service instructors (8 adult males and 23 females) with a historical past in laptop science and training at an instructor coaching university. Before the beginning of the experiment, the learn-about topics were randomly assigned to the experimental crew (16) and the management team (15). Before the beginning of the experiment, the experimental crew used to be skilled in wholly apprehending the features and use of the studying evaluation tool. During the experiment, the research subjects, as online collaborative learning teachers, supervised and intervened in the online collaborative discussions of six groups of students on the Moodle platform simultaneously. Among them, the experimental group could monitor the collaborative learning of the learning groups by viewing the discussion contents in conjunction with the learning analysis tool at any time; the control group could only monitor the collaborative learning of the learning groups through the discussion contents. When the teacher finds that a learning group needs intervention, the intervention content is sent to the corresponding group; when multiple groups need intervention, the intervention content is sent to the whole class. The length of the experiment was the same as the real classroom, 90 minutes. The entire experiment was recorded on video to ensure a complete recording of the process data. At the end of the experiment, the researcher interviewed the teacher about the process of collaborative learning intervention.

3.3 Data Collection and Analysis

This study focused on coding and analyzing the content of teacher interventions using content analysis. Combining Leeuwen et al.'s researcher's coding sheet for teacher intervention modality and intervention target [27] and Furberg et al.'s coding sheet for learner problem classification, the coding sheet for teacher intervention concerns, intervention modality, and intervention target was finalized (as shown in Table 2). First, two researchers jointly sliced the meaningful units of the intervention according to the meaning of the content of the teacher intervention. And then, 10 study participants (30% of the overall study participants) were randomly selected for the content of the intervention, and the two researchers coded the three dimensions of intervention concerns, intervention modalities, and intervention targets according to the coding table [28]. The coding consistency between the two coders on the three dimensions was then tested, and the coding consistency for the three dimensions was obtained as 0.90, 0.77, and 0.82, respectively. The two researchers discussed and agreed on the areas where there were differences in coding. The final remaining intervention content was completed, coded by one researcher, and statistically analyzed [29].

Table 2: Coding of teacher intervention focus, approach, and targets

Dimension	Category	Definition	Example
Focus	Cognitive	Focus on knowledge understanding and task completion.	I don't understand the concept of queue yet.
	Cognitive Regulation	Focus on knowledge understanding and task completion strategies.	The progress is too slow.
	Social	Focus on people engagement and communication.	Everyone grasps the time.
	Social Conditioning	Focus on people organization and coordination strategies.	Rapidly participate in the discussion of everyone involved and share the work.
	Other	Focus on non-collaborative learning content such as system use.	Reply, do not open a new topic.
Approach	Diagnosis	The status of task resolution.	Can you distinguish between a stack and a queue?
	Prompting	Asking students about knowledge processing and tasks.	Consider the location of the staging to remove the goods.
	Explaining	Giving students certain hints and not explicitly telling them the answers.	The queue is first in, first out!
	Guiding	Giving students definite explanations or answers.	Read the question again to clarify the meaning.
	Encourage	Actively encouraging and affirming student performance.	The student's idea is very good.
	Criticism	Negatively evaluates student performance.	The theory of inches is off topic again.
Target	Individual	Focus on the problems and progress of one person.	Hurry up and join the discussion!
	Group	Focus on the problems and progress of multiple people in a group.	The progress is too slow; let's hurry up.
	Class	Focus on the problems and progress of multiple groups.	Many groups are not understanding the problem.

4 Experimental Results

4.1 Learning Engagement Analysis

After the learning engagement analysis experiment, in order to understand the online engagement of learners in each class, the platform data were quantified based on the previously designed rubrics, and due to a large number of learners, the quality assessment of online learning engagement required the researcher to manually count them one by one [30]. Therefore, simple random sampling was adopted at this stage, and the online learning records of 20 learners in each of the experimental and control groups were selected as the data source.

From Figure 7, we can see that the overall participation scores of the experimental class were all above 400, which was in the middle to the upper level, but there was a large difference between the highest and lowest scores, and there was a phenomenon of uneven participation. The learners numbered S3 had the highest scores and were the core participants of the course, with significantly higher post counts, average learning intervals, and teacher-led feedback than the rest of the learners

[31]. Learners numbered S5 and S9 scored higher, had a higher number of posts and replies, had good quality posts, were important participants in the online course, actively engaged in forum interactions, and shared their personal views for knowledge construction. Learners numbered S19 have the lowest scores, indicating that they are not enthusiastic about participating in the course and are marginal participants in this course.

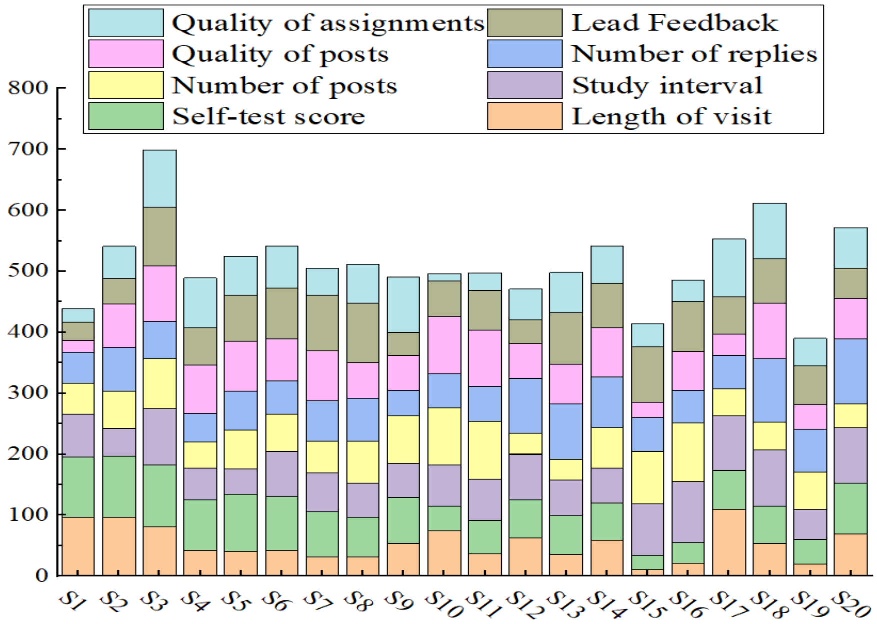

Fig. 7: Learner engagement in the experimental group

The data of the four participants with large differences in participation were sampled, and radar plots were drawn to reflect the scores of each indicator more visually, as shown in Figure 8. Learners numbered S3 actively participated in all learning activities, took the teacher's guidance and feedback seriously, completed the assigned assignments efficiently and with high quality, were often active in the forum area [32], put forward constructive opinions, and were important participants. The learner numbered S10 was poor in completing assignments, had a low number of posts, and needed to improve his ability to identify problems; the learner numbered S12 was active in interacting with other peers, though. However, the actual posts were not very inspiring, the length of access to course resources was short, and learning was easily delayed. The learner numbered S19 did well on the self-assessment questions, but his overall participation was not high, especially when the posts were heavily flooded, probably with "followers" and "water posts," and his learning attitude was rather perfunctory, requiring special attention from the teacher.

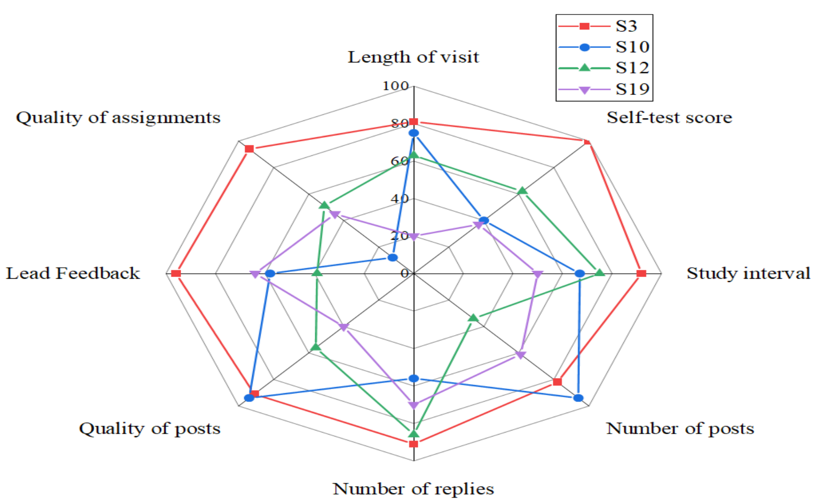

Fig. 8: Online engagement of some learners

4.2 Contrast Analysis

The mean values of each evaluation index were compared between the experimental group and the control group, and the data shown in Table 3 were obtained. There is no major difference between the two at the level of access length, self-assessment question scores, and instructor-led feedback. The reason may be that this course requires learners to watch and complete all videos at the end of the semester, and they will consciously comply with the assessment rules. At the same time, the course is a general elective course, which needs to be taught to learners of different grades, majors, and knowledge bases, and is designed to popularize the basics of entrepreneurship and stimulate entrepreneurial awareness. Thus, the self-assessment questions are relatively easy; and the teacher's guided feedback is to help learners better participate in the course, and learners are generally active and cooperative [33]. On the other hand, the teacher will top the excellent posts to give learners an exemplary role and raise their perceived standard of good forum statements. The experimental group scored significantly higher than the control group in terms of assignment scores, reflecting the learners' better knowledge and the excellent examples provided by the teacher to help them identify areas for improvement and revise them to enhance the quality of their learning outcomes.

Table 3: Comparison of mean values of online engagement evaluation indicators

	Length of interview	Self-test questions Score	Average study interval	Average study interval	Number of replies	Quality of posts	Feedback	Assignments Score
Experimental group	636min	97.5	6480min	3	3.47	68.5	63.79	71.33
Control group	634min	97	7599min	2	1	61	63.33	66

4.3 Independent Samples T-test

To investigate the effectiveness of the intervention strategy, an independent samples t-test was done using SPSS for the online learning participation of the experimental and control groups. First, the normality check used to be carried out, and the outcomes were acquired as proven in Table 4, which confirmed that the p-values of Shapiro-Wilk for the two training have been 0.689 and 0.225, respectively, which have been each higher than 0.05, indicating that the records inside the crew have been shut to an everyday distribution.

Table 4: Standing check of online learning participation

	Groups	Kolmogorov-Smirnova			Shapiro-Wilk		
		Statistics	df	Significance	Statistics	df	Significance
Score	Experimental group	133	20	0.200	967	20	0.689
	Control group	166	20	0.150	939	20	0.225

In this study, the implied online engagement of newbies in the experimental team used to be 72.75, and the suggested online engagement of rookies in the managed team used to be 63.82, as proven in Table 5, indicating that rookies in the experimental crew were greater engaged. The consequences of the unbiased pattern t-test are proven in Table 6. The p-value of the chi-square check is 0.538, which is larger than 0.05, indicating that there is no considerable distinction between the variances of the two groups, and the p-value of the t-test is 0.031, which is much less than 0.05, indicating that there is a substantial distinction between the potential of online engagement of the newbies in the experimental and manage groups. In summary, it can be concluded that the intervention approach can beautify the online engagement of learners.

Table 5: Descriptive statistics of online learning engagement

	Groups	N	Average	Standard Deviation	Standard error mean
score	Experimental group	20	72.7510	13.51.52	3.02104
	Control group	20	63.8205	11.69264	2.61455

Table 6: Independent presents t-test statistics of online learning participation

<table>
<tr><td rowspan="2"></td><td rowspan="2">Levene's variance coefficient of variation equality test</td><td colspan="9">t-test for equality of means</td></tr>
<tr><td>F</td><td>Sig</td><td>t</td><td>df</td><td>Sig</td><td>Mean Difference</td><td>Standard error value</td><td>Min.</td><td>Max.</td></tr>
<tr><td rowspan="2">score</td><td>Assume equal variances</td><td>0.387</td><td>0.538</td><td>2.235</td><td>38</td><td>0.031</td><td>8.93050</td><td>3.99532</td><td>0.84239</td><td>17.01861</td></tr>
<tr><td>Assume unequal variances</td><td colspan="2">1.305</td><td>2.235</td><td>37.233</td><td>0.031</td><td>8.93050</td><td>3.99532</td><td>0.83692</td><td>17.02408</td></tr>
</table>

The research shows that there is a positive correlation between learning performance and online learning participation. The research shows that there is a positive correlation between learning performance and online learning participation. According to the functions of the teaching platform and relevant operational guidelines, eight data representing learning engagement in distance education are extracted, and correlation analysis is conducted with learning performance respectively. Through empirical research, it is concluded that the remaining seven items except Posting participation are positively correlated with learning performance. By analyzing the interaction and effect relationship among learners' information literacy, online learning engagement and online learning performance, it is found that online learning engagement can directly and positively affect online learning performance. Therefore, this study collected the final scores of the experimental group and the control group to further test the improvement of online learning participation from the side. After normality test results, it can be seen that the P values of Shapiro-Wilk in both classes are greater than 0.05, indicating that the data in the group is close to normal distribution.

5 Conclusion and Insights

The main shortcomings of this study are: the representation of learning analytics in classroom interactions needs to be strengthened, the tool can only use learning analytics for basic analysis of classroom interaction data at present, and the functions such as learning improvement suggestions and classroom monitoring for students and teachers cannot be realized yet: the types of classroom interactions provided by the tool are limited, and teachers have limited choices in conducting classroom interaction activities. The next step of this study will be to conduct more investigations on the above issues, design and develop more classroom interaction activities to provide teachers with more choices and broaden the width and depth of the application of learning analytics in classroom interactions to provide more help to students and teachers.

This study collates theories and research related to learning analytics and classroom interaction and summarizes the development of applications related to learning analytics and classroom interaction. Based on this, this study designed and developed a classroom interaction tool supported by learning analytics and tested and applied the tool. In summary, the main research results and innovations of this study are as follows.

1. collating and summarizing the current Research and applications related to learning analytics and classroom interaction, which provides a basis for subsequent classroom interaction-related research.

2. The analysis methods commonly used in classroom interaction are summarized, the real-time response analysis method and classroom interaction behavior analysis method supported by learning analytics are proposed, and the related results are visualized.

3. Applying learning analytics to analyze data generated from classroom interactions, we provide students with learning dashboards and teachers with classroom interaction tools, S-T analysis tools, and Rt-Ch analysis tools to help students and teachers deepen their understanding of data related to course interactions. We designed and implemented a classroom interaction tool for college classrooms based on WeChat public website with certain convenience and practical use.

The advantages of implementing online learning intervention with the support of learning analysis technology lie in the easy access to learning data. The online platform has a complete record of the learning process, providing rich data sources for the research. Secondly, based on the data analysis results, the prediction of learning risks and the screening of intervention objects are more accurate, and the decisions are made more scientifically. With the support of learning analysis technology, automatic intervention can be partially realized to reduce the workload of manual pre-processing; Finally, the intervention strategy with the support of learning analysis technology is more targeted to overcome learning disabilities, which ensures the realization of the effect of learning intervention.

6 Recommendations

The research recommends activating the role of Blackboard system in Saudi universities in light of crises, in general, and Coronavirus pandemic in particular, due to its positive impact in this field as well as conducting relevant researches.

Conflicts of Interest Statement

The authors certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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